EXP NO: 1	Install Apache Hadoop
Date:	

AIM: To Install Apache Hadoop software on Windows.

Hadoop software can be installed in three modes of Hadoop is a Java-based programming framework that supports the processing and storage of extremely large datasets on a cluster of inexpensive machines. It was the first major open-source project in the big data playing field and is sponsored by the Apache Software Foundation.

Hadoop-2.7.3 is comprised of four main layers:

- **Hadoop Common** is the collection of utilities and libraries that support other Hadoop modules.
- **HDFS**, which stands for Hadoop Distributed File System, is responsible for persisting data to disk.
- **YARN**, short for Yet Another Resource Negotiator, is the "operating system" for HDFS.
- **MapReduce** is the original processing model for Hadoop clusters. It distributes work within the cluster or map, then organizes and reduces the results from the nodes into a response to a query. Many other processing models are available for the 2.x version of Hadoop.

Hadoop clusters are relatively complex to set up, so the project includes a stand-alone mode which is suitable for learning about Hadoop, performing simple operations, and debugging.

Procedure:

we'll install Hadoop in stand-alone mode and run one of the example MapReduce programs it includes to verify the installation.

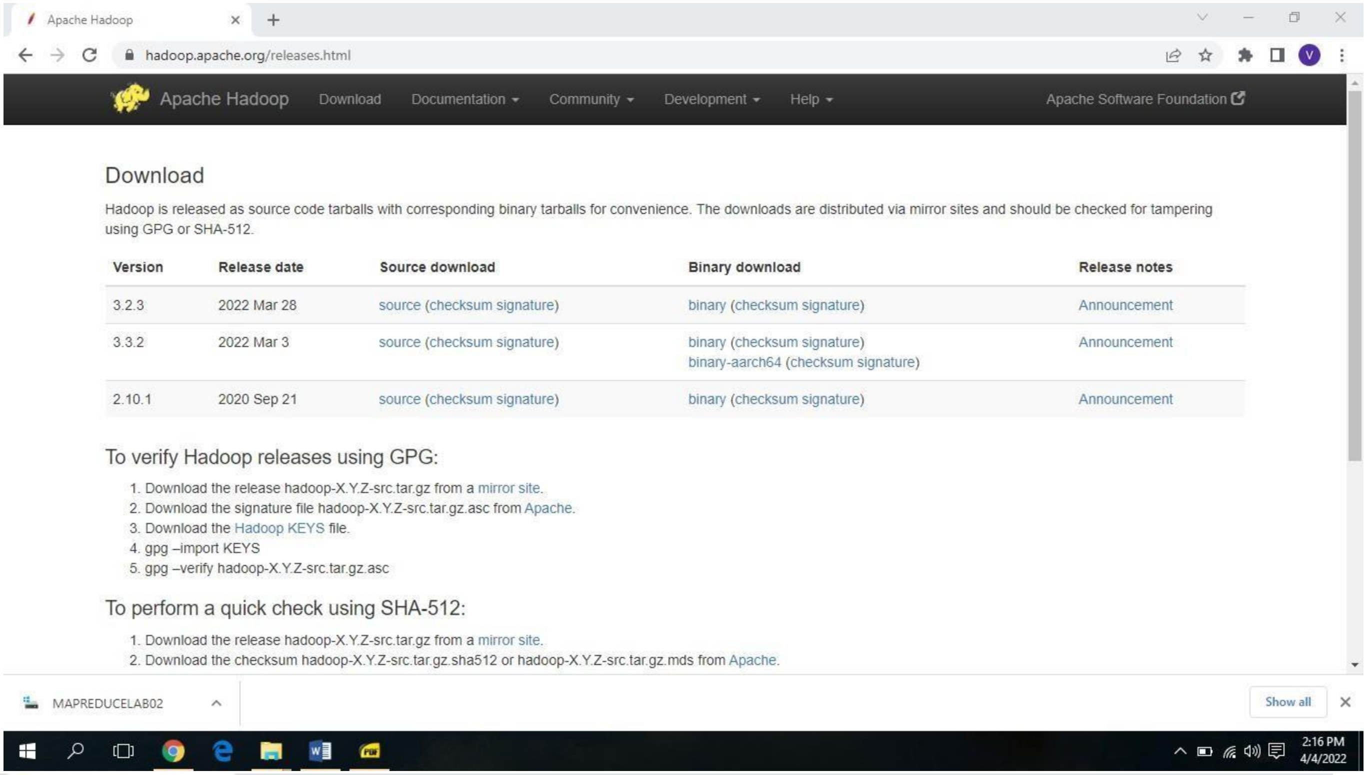
Prerequisites:

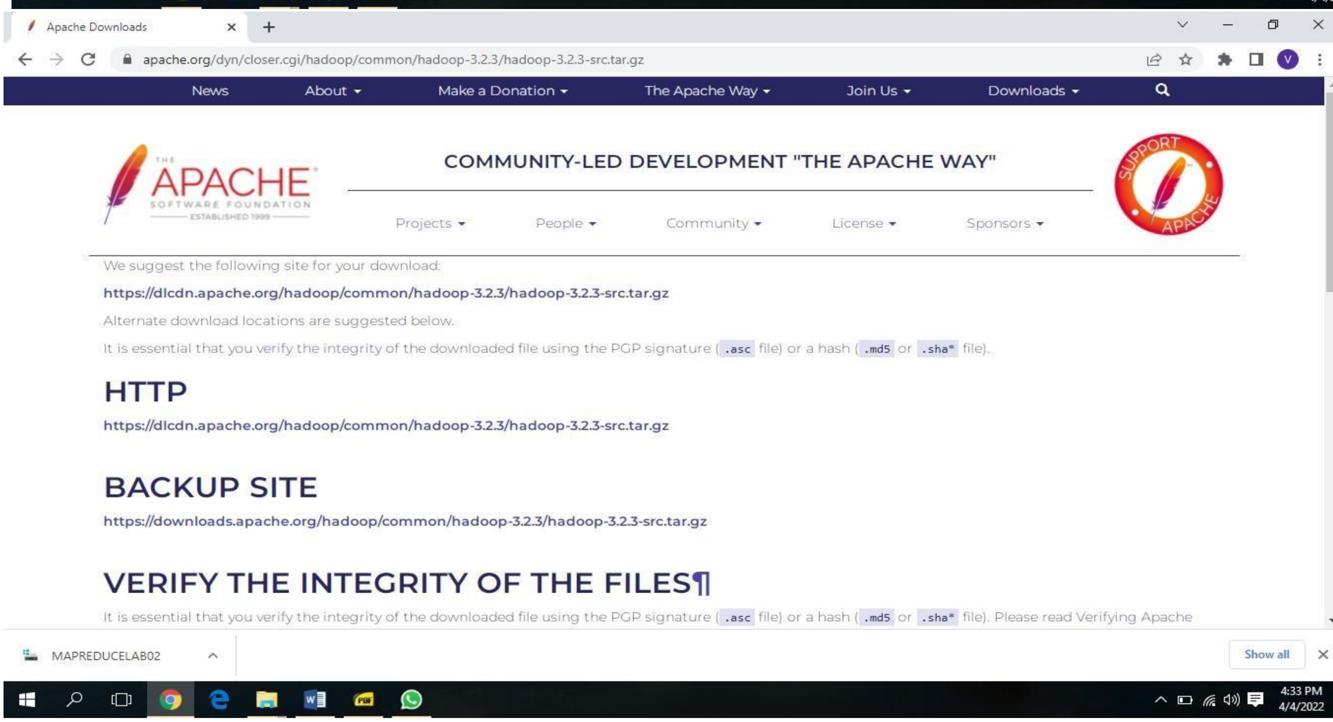
Step1: Installing Java 8 version.

Openjdk version "1.8.0_91"
OpenJDK Runtime Environment (build 1.8.0_91-8u91-b14-3ubuntu1~16.04.1-b14)
OpenJDK 64-Bit Server VM (build 25.91-b14, mixed mode) This output verifies that OpenJDK has been successfully installed.
Note: To set the path for environment variables. i.e. JAVA_HOME

Step2: Installing Hadoop
With Java in place, we'll visit the Apache Hadoop Releases page to find the most recent stable release. Follow the binary for the current release:

Download Hadoop from www.hadoop.apache.org





Procedure to Run Hadoop

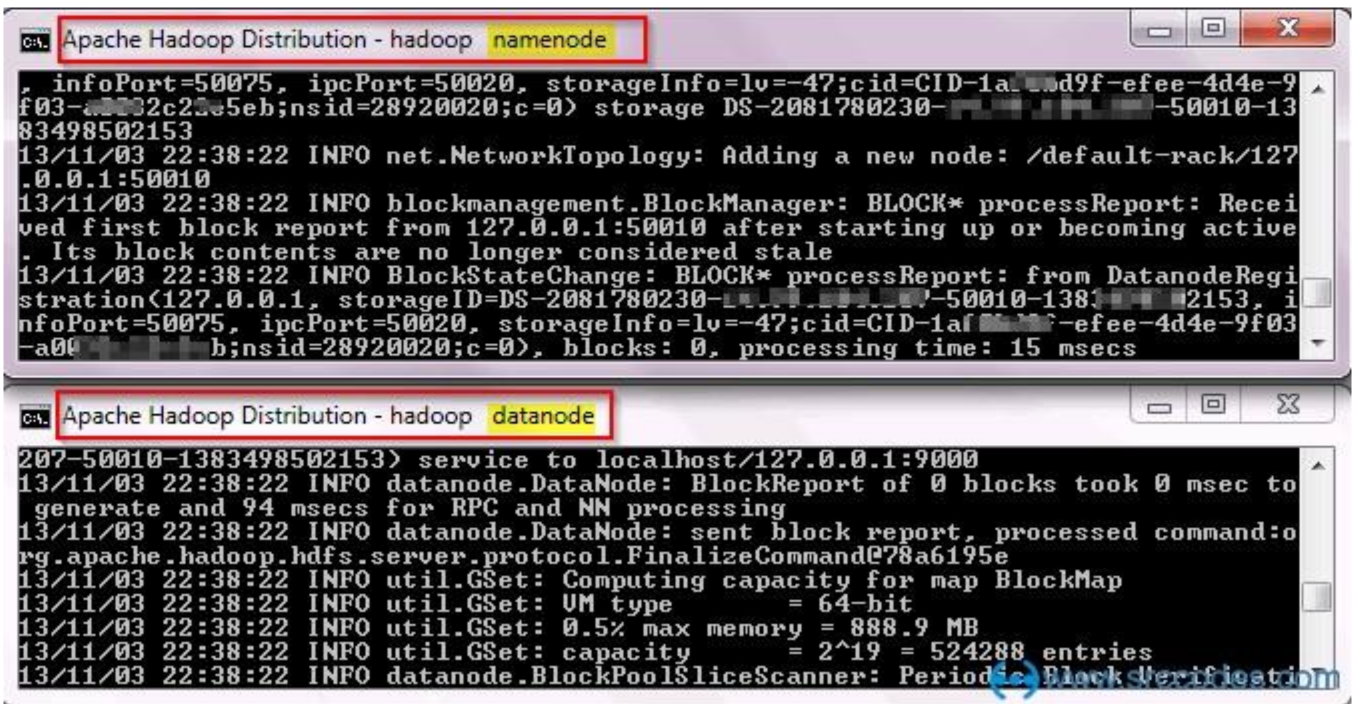
1. Install Apache Hadoop 2.2.0 in Microsoft Windows OS

If Apache Hadoop 2.2.0 is not already installed then follow the post Build, Install, Configure and Run Apache Hadoop 2.2.0 in Microsoft Windows OS.

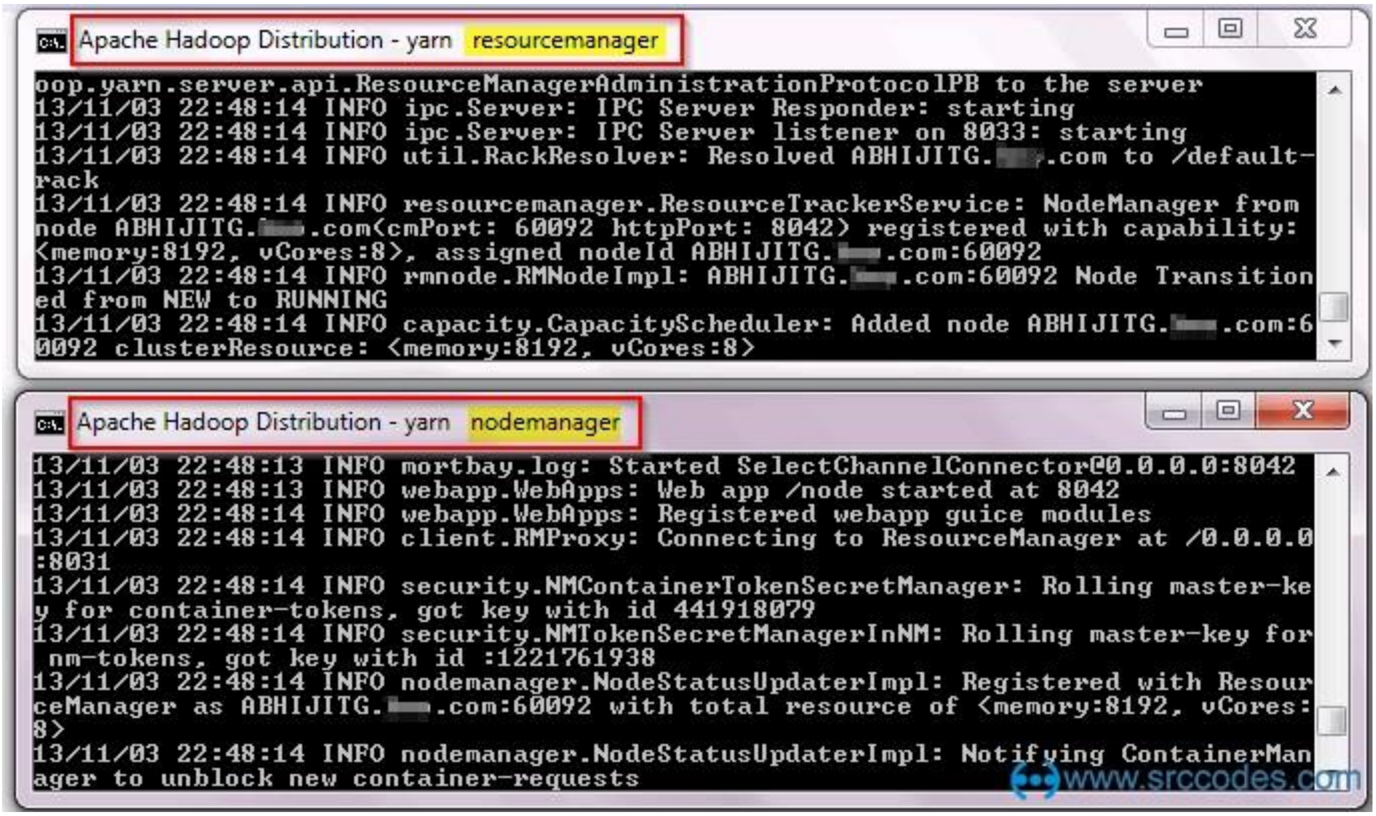
2. Start HDFS (Namenode and Datanode) and YARN (Resource Manager and Node Manager)

Run following commands.
Command Prompt
C:\Users\abhijitg>cd c:\hadoop
c:\hadoop>sbin\start-dfs
c:\hadoop>sbin\start-yarn starting yarn daemons

Namenode, **Datanode**, **Resource Manager** and **Node Manager** will be started in few minutes and ready to execute Hadoop **MapReduce** job in the Single Node (pseudo-distributed mode) cluster.



Resource Manager & Node Manager:



Run wordcount MapReduce job

Now we'll run **wordcount** MapReduce job available in

%HADOOP_HOME%\share\hadoop\mapreduce\hadoop-mapreduce-examples- 2.2.0.jar

Create a text file with some content. We'll pass this file as input to the **wordcount** MapReduce job for counting words.

C:\file1.txt

```
Install  Hadoop
```

```
Run  Hadoop  Wordcount  Mapreduce  Example
```

Create a directory (say 'input') in HDFS to keep all the text files (say 'file1.txt') to be used for counting words.

C:\Users\abhijitg>cd c:\hadoop
C:\hadoop>bin\hdfs dfs -mkdir input

Copy the text file (say 'file1.txt') from local disk to the newly created 'input' directory in HDFS
C:\hadoop>bin\hdfs dfs -copyFromLocal c:/file1.txt input

Check content of the copied file.

C:\hadoop>hdfs dfs -ls input

Found 1 items
-rw-r--r-- 1 ABHIJITG supergroup 55 2014-02-03 13:19 input/file1.txt

C:\hadoop>bin\hdfs dfs -cat input/file1.txt

Install Hadoop
Run Hadoop Wordcount Mapreduce Example

Run the wordcount MapReduce job provided in

%HADOOP_HOME%\share\hadoop\mapreduce\hadoop-mapreduce-examples-2.2.0.jar

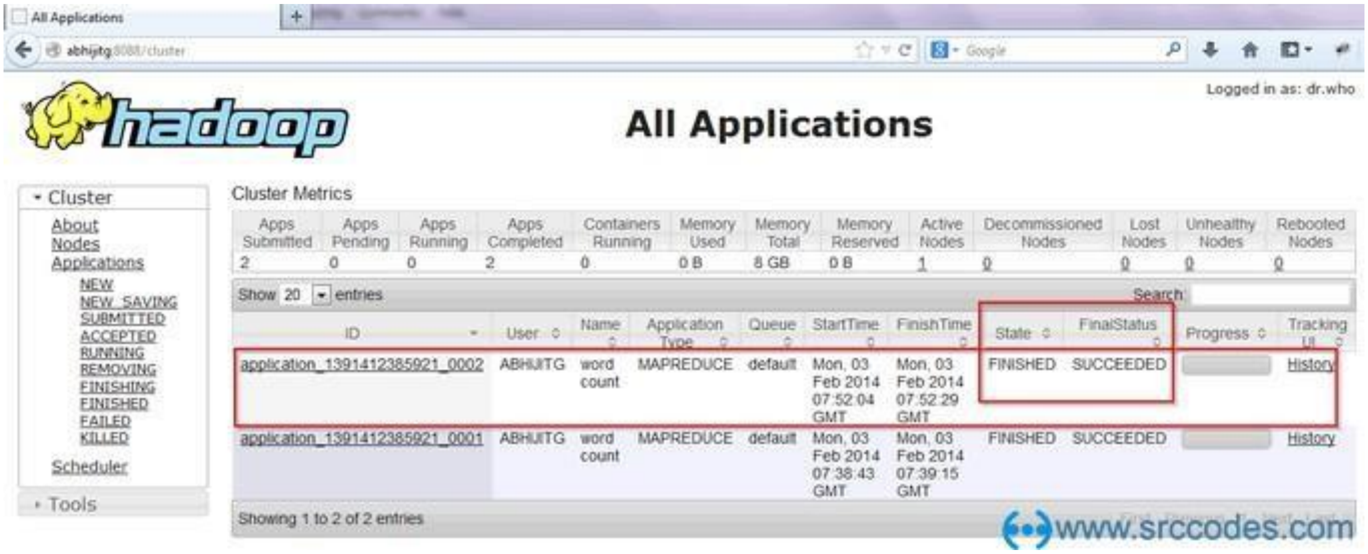
C:\hadoop>bin\yarn jar share/hadoop/mapreduce/hadoop-mapreduce-examples- 2.2.0.jar

wordcount input output

14/02/03 13:22:02 INFO client.RMProxy: Connecting to ResourceManager at
/0.0.0.0:8032
14/02/03 13:22:03 INFO input.FileInputFormat: Total input paths to process: 1 14/02/03 13:22:03
INFO mapreduce.JobSubmitter: number of splits:1
:
:
14/02/03 13:22:04 INFO mapreduce.JobSubmitter: Submitting tokens for job:
job_1391412385921_0002
14/02/03 13:22:04 INFO impl.YarnClientImpl: Submitted application
application_1391412385921_0002 to ResourceManager at /0.0.0.0:8032 14/02/03
13:22:04 INFO mapreduce.Job: The url to track the job:
http://ABHIJITG:8088/proxy/application_1391412385921_0002/
14/02/03 13:22:04 INFO mapreduce.Job: Running job: job_1391412385921_0002 14/02/03
13:22:14 INFO mapreduce.Job: Job job_1391412385921_0002 running in uber mode: false
14/02/03 13:22:14 INFO mapreduce.Job: map 0% reduce 0%
14/02/03 13:22:22 INFO mapreduce.Job: map 100% reduce 0%
14/02/03 13:22:30 INFO mapreduce.Job: map 100% reduce 100%
14/02/03 13:22:30 INFO mapreduce.Job: Job job_1391412385921_0002 completed successfully
14/02/03 13:22:31 INFO mapreduce.Job: Counters: 43 File
System Counters
FILE: Number of bytes read=89
FILE: Number of bytes written=160142 FILE:
Number of read operations=0 FILE: Number of
large read operations=0 FILE:
Number of write operations=0
HDFS: Number of bytes read=171
HDFS: Number of bytes written=59

HDFS: Number of read operations=6
HDFS: Number of large read operations=0 HDFS:
Number of write operations=2
Job Counters
Launched map tasks=1 Launched
reduce tasks=1
Data-local map tasks=1
Total time spent by all maps in occupied slots (ms)=5657 Total time spent
by all reduces in occupied slots (ms)=6128
Map-Reduce Framework Map input
records=2 Map output
records=7 Map output
bytes=82
Map output materialized bytes=89 Input split
bytes=116
Combine input records=7
Combine output records=6
Reduce input groups=6
Reduce shuffle bytes=89
Reduce input records=6 Reduce output
records=6
Spilled Records=12 Shuffled
Maps =1
Failed Shuffles=0 Merged
Map outputs=1
GC time elapsed (ms)=145 CPU time
spent (ms)=1418
Physical memory (bytes) snapshot=368246784 Virtual memory
(bytes) snapshot=513716224 Total committed
heap usage (bytes)=307757056
Shuffle Errors
BAD_ID=0 CONNECTION=0
IO_ERROR=0
WRONG_LENGTH=0 WRONG_MAP=0
WRONG_REDUCE=0
File Input Format Counters Bytes Read=55
File Output Format Counters
Bytes Written=59

http://abhijitg:8088/cluster



Result: We has been successfully installed Hadoop in stand-alone mode and verified it by running an example program which is provided.

EXP NO: 2	MapReduce program to calculate the frequency
Date:	

AIM: To Develop a MapReduce program to calculate the frequency of a given word in a given file **Map Function** – It takes a set of data and converts it into another set of data, where individual elements are broken down into tuples (Key-Value pair).

Example – (Map function in Word Count)

Input

Set of data

Bus, Car, bus, car, train, car, bus, car, train, bus, TRAIN, BUS, buS, caR, CAR, car, BUS, TRAIN

Output

Convert into another set of data

(Key,Value)

(Bus,1), (Car,1), (bus,1), (car,1), (train,1), (car,1), (bus,1), (car,1), (train,1), (bus,1), (TRAIN,1), (BUS,1), (buS,1), (caR,1), (CAR,1), (car,1), (BUS,1), (TRAIN,1)

Reduce Function – Takes the output from Map as an input and combines those data tuples into a smaller set of tuples.

Example – (Reduce function in Word Count)

Input Set of Tuples

(output of Map function)

(Bus,1), (Car,1), (bus,1), (car,1), (train,1), (car,1), (bus,1), (car,1), (train,1), (bus,1), (TRAIN,1), (BUS,1), (buS,1), (caR,1), (CAR,1), (car,1), (BUS,1), (TRAIN,1)

Output Converts into smaller set of tuples

(BUS,7), (CAR,7), (TRAIN,4)

Workflow of Program

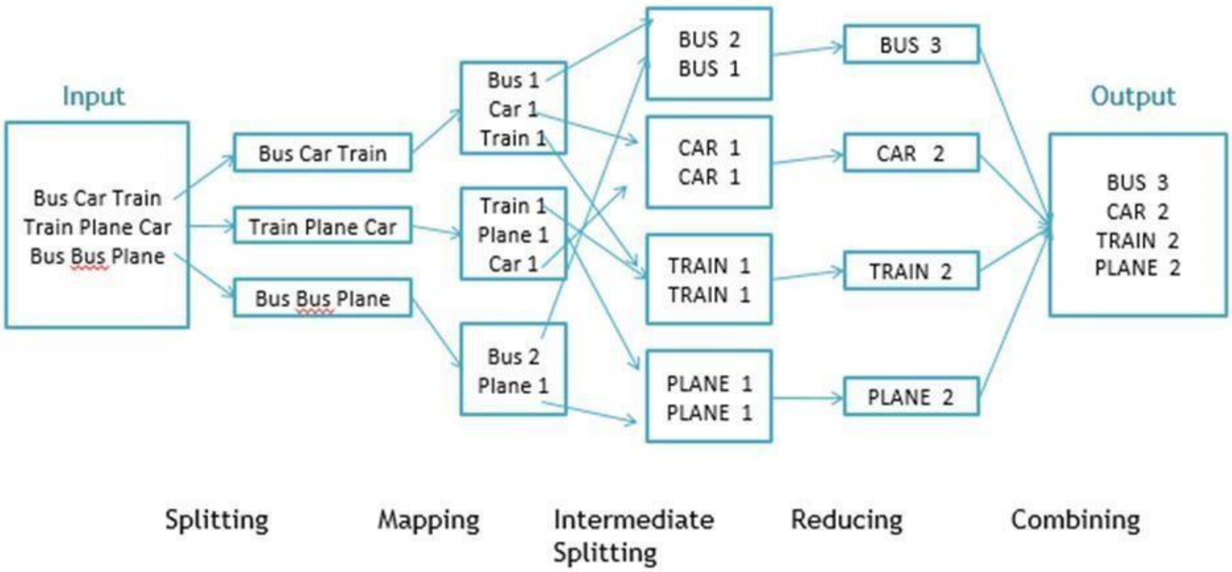


Fig. WorkFlow of MapReducing

Workflow of MapReduce consists of 5 steps

1. Splitting – The splitting parameter can be anything, e.g. splitting by space, comma, semicolon, or even by a new line (‘\n’). 2. **Mapping –** as explained above

3. Intermediate splitting – the entire process in parallel on different clusters. In order to group them in "Reduce Phase" the similar KEY data should be on same cluster.
4. **Reduce –** it is nothing but mostly group by phase
5. **Combining –** The last phase where all the data (individual result set from each cluster) is combined together to form a Result

Now Let's See the Word Count Program in Java

Make sure that Hadoop is installed on your system with java idk Steps to follow

Step 1. Open Eclipse> File > New > Java Project > (Name it – MRProgramsDemo) > Finish
Step 2. Right Click > New > Package (Name it - PackageDemo) > Finish
Step 3. Right Click on Package > New > Class (Name it - WordCount)
Step 4. Add Following Reference Libraries –

Right Click on Project > Build Path> Add External Archivals

- /usr/lib/hadoop-0.20/hadoop-core.jar
- Usr/lib/hadoop-0.20/lib/Commons-cli-1.2.jar

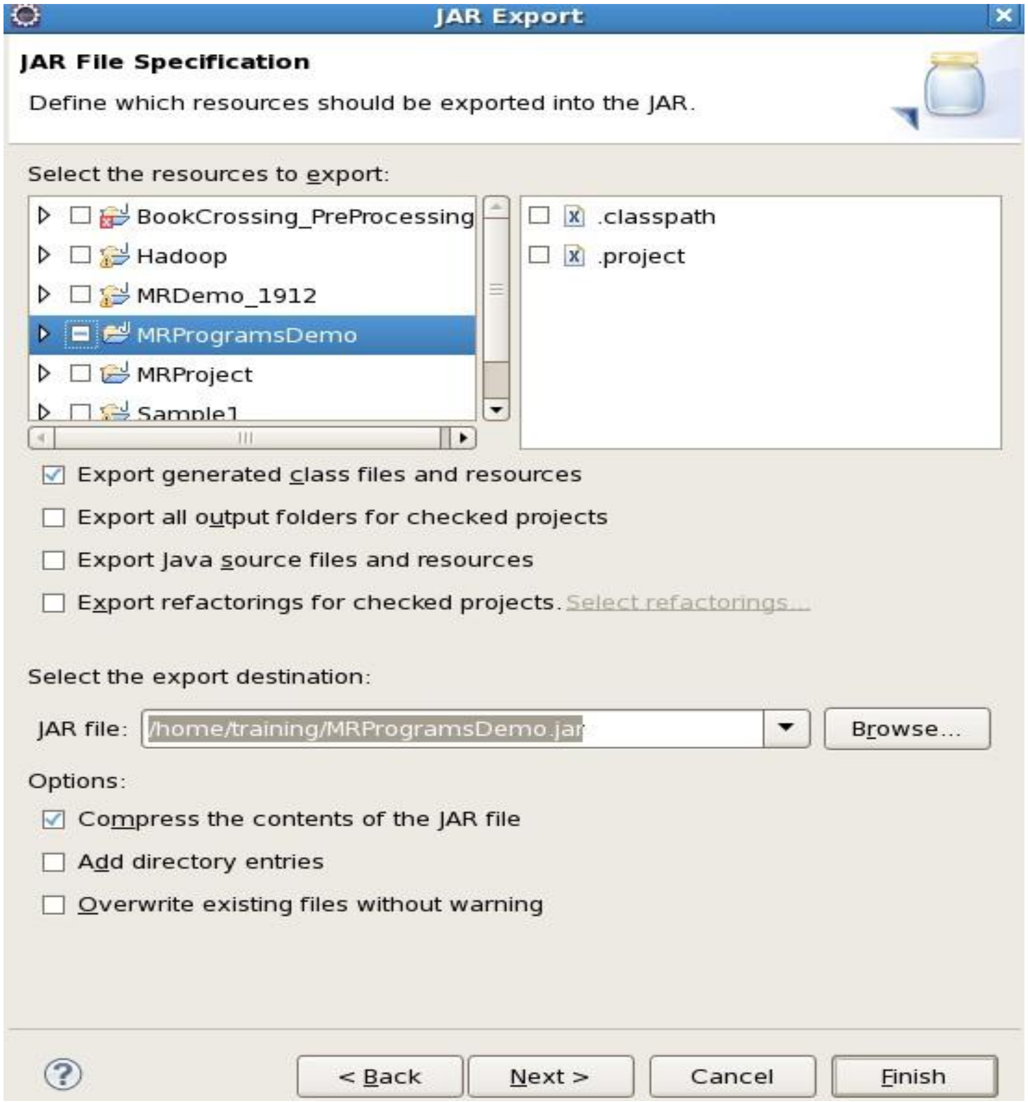
Program: Step 5. Type following Program:

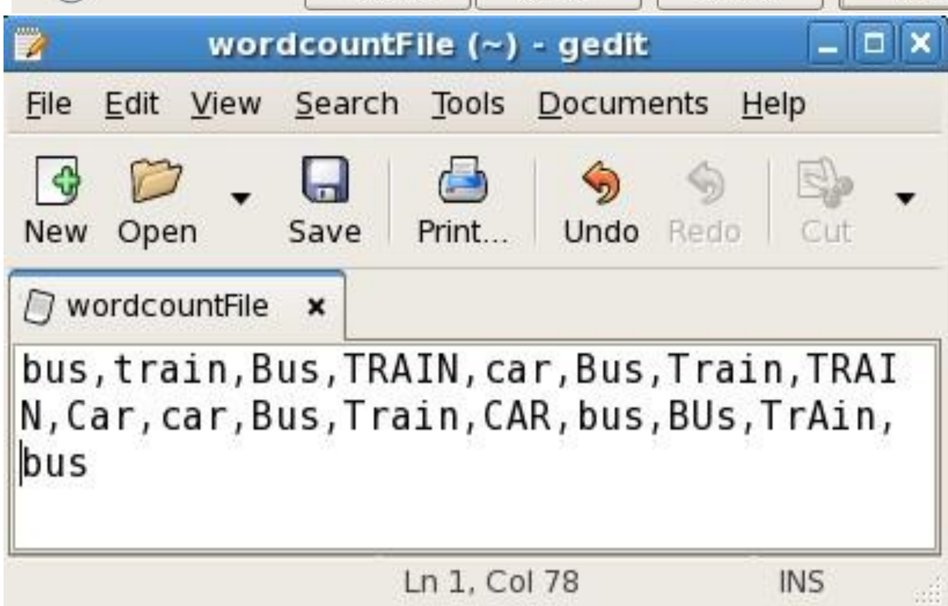
```
package Packaged Emo; import java.io.IOException;
import            org.apache.hadoop.conf.Configuration;
import                    org.apache.hadoop.fs.Path;                    import
org.apache.hadoop.io.IntWritable;                                       import
org.apache.hadoop.io.LongWritable;                                      import
org.apache.hadoop.io.Text;                                              import
org.apache.hadoop.mapreduce.Job;                                        import
org.apache.hadoop.mapreduce.Mapper;                                     import
org.apache.hadoop.mapreduce.Reducer;                                    import
org.apache.hadoop.mapreduce.lib.input.FileInputFormat;        import
org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;    import
org.apache.hadoop.util.GenericOptionsParser;

public class WordCount {

public static void main (String [] args) throws Exception
{
Configuration c=new Configuration ();
String [] files=new GenericOptionsParser(c,args).getRemainingArgs();

Path input=new Path (files [0]);
Path output=new Path (files [1]);

Job     j=new      Job(c,"wordcount");
j.setJarByClass(WordCount.class);

j.setMapperClass(MapForWordCount.class);
j.setReducerClass(ReduceForWordCount.class);

j.setOutputKeyClass(Text.class);
j.setOutputValueClass(IntWritable.class);

 FileInputFormat.addInputPath(j,                              input);
 FileOutputFormat.setOutputPath(j,                           output);
System.exit(j.waitForCompletion(true)?0:1);
}
public static class MapForWordCount extends Mapper<LongWritable, Text, Text, IntWritable> {

   public void map       (LongWritable      key, Text       value, Context           con) throws IOException,
InterruptedException


{
String line = value.toString();
String [] words=line.split(",");
```

```
for (String word: words)
{
    Text outputKey = new Text(word.toUpperCase(). trim ()); IntWritable
      outputValue    =         new     IntWritable(1);
    con.write(outputKey, outputValue);
}
}
}

public static class ReduceForWordCount extends Reducer<Text, IntWritable, Text, IntWritable>
{
public void reduces (Text word, Iterable<IntWritable> values, Context con) throws IOException,

InterruptedException
{ int sum =
0;
for (IntWritable value: values)
{
sum += value.get();
}
con.write(word, new IntWritable(sum));
}
}
}
```

Make Jar File

Right Click on Project> Export> Select export destination as Jar File > next> Finish


JAR Export
JAR File Specification
Define which resources should be exported into the JAR.
Select the resources to export:
BookCrossing_PreProcessing
Hadoop
MRDemo_1912
MRProgramsDemo
MRProject
Sample1
.classpath
.project
Export generated class files and resources
Export all output folders for checked projects
Export Java source files and resources
Export refactorings for checked projects. Select refactorings...
Select the export destination:
JAR file: /home/training/MRProgramsDemo.jar
Browse...
Options:
Compress the contents of the JAR file
Add directory entries
Overwrite existing files without warning
< Back
Next >
Cancel
Finish


wordcountFile (~) - gedit
File Edit View Search Tools Documents Help
New Open Save Print... Undo Redo Cut
wordcountFile
bus,train,Bus,TRAIN,car,Bus,Train,TRAIN,Car,car,Bus,Train,CAR,bus,BUs,TrAin,bus
Ln 1, Col 78
INS

To Move this into Hadoop directly, open the terminal and enter the following commands:

[training@localhost ~] $ hadoop fs -put wordcountFile wordCountFile

Run Jar file

(Hadoop jar jarfilename.jar packageName.ClassName PathToInputTextFile PathToOutputDirectry)

[training@localhost ~] $ Hadoop jar MRProgramsDemo.jar PackageDemo.WordCount wordCountFile MRDir1

Result: Open Result

[training@localhost ~] $ hadoop fs -ls MRDir1

Found 3 items
-rw-r--r-- 1 training supergroup
0 2016-02-23 03:36 /user/training/MRDir1/_SUCCESS
drwxr-xr-x - training supergroup
0 2016-02-23 03:36 /user/training/MRDir1/_logs
-rw-r--r-- 1 training supergroup
20 2016-02-23 03:36 /user/training/MRDir1/part-r-00000

[training@localhost ~] $ hadoop fs -cat MRDir1/part-r-00000

BUS 7
CAR 4
TRAIN 6

Result: MapReduce program to calculate the frequency is executed successfully.

EXP NO: 3	**Implement MapReduce program that processes a weather dataset**
Date:	

AIM: The aim is to Implement MapReduce program that processes a weather dataset.

Procedure:

- The code simulates weather data with random temperature and humidity values.
- It defines map functions to categorize temperature and humidity data into key-value pairs.
- A reduce function aggregates the mapped data by summing up the values for each key.
- The MapReduce function combines mapping and reducing operations:
- It maps the data using a specified mapper function.
- It groups the mapped data by keys.
- It reduces each group using a reducer function.
- In the main execution:
- Simulated weather data is generated.
- MapReduce is performed separately for temperature and humidity.
- The counts of temperature and humidity values are printed as output.

Program: import

```
random
from multiprocessing import Pool

# Simulated weather data generator def
generate_weather_data(num_records):
   weather_data = []     for _ in
range(num_records):        temperature =
random.randint(-20, 40)        humidity =
random.randint(0, 100)
weather_data.append((temperature, humidity))
return weather_data
# Map function to process temperature data
def map_temperature(data):
temperature, humidity = data     return
temperature, 1
#Map function to process humidity data def
map_humidity(data):
   temperature, humidity = data
return humidity, 1
# Reduce function to aggregate counts def
reduce_counts(data):
   key, counts = data
```

```
    return key, sum(counts)
# MapReduce function


def map_reduce(data, mapper, reducer):
mapped_data = [mapper(item) for item in data]
grouped_data = {}     for key, value in
mapped_data:        grouped_data.setdefault(key, []).
append(value)
    reduced_data = [reducer ((key, value)) for key, value in grouped_data.items()]
return reduced_data

if __name__ == '__main__':
# Simulate weather dataset
    weather_data = generate_weather_data(1000)

    # Run MapReduce for temperature
    temperature_counts = map_reduce(weather_data, map_temperature, reduce_counts)
print ("Temperature counts:")
    print(temperature_counts)

    # Run MapReduce for humidity
    humidity_counts = map_reduce(weather_data, map_humidity, reduce_counts)
print ("Humidity counts:")     print(humidity_counts)
```

OUTPUT:

Temperature counts:

[(-8, 15), (22, 18), (30, 13), (4, 18), (15, 12), (36, 17), (17, 17), (-13, 20), (39, 18), (3, 13), (27, 13), (-2, 12), (7, 18), (0, 15), (-16, 15), (-20, 20), (-9, 22), (16, 22), (28, 16), (40, 15), (23, 13), (-11, 19), (1, 24), (2, 24), (8, 23), (-18, 24), (-19, 16), (11, 17), (-10, 26), (-7, 17), (19, 15), (-4, 12), (6, 21), (-3, 16), (31, 15), (-14, 14), (12, 20), (-6, 19), (18, 10), (26, 13), (5, 9), (-1, 15), (29, 14), (20, 19), (-12, 14), (32, 13), (-15, 18), (9, 22), (14, 15), (38, 13), (13, 21), (33, 20), (25, 13), (35, 16), (10, 11), (37, 18), (21, 14), (24, 16), (34, 15), (-17, 7), (-5, 10)]

Humidity counts:

[(27, 10), (49, 9), (98, 13), (5, 10), (86, 12), (43, 7), (42, 10), (54, 11), (62, 8), (77, 16), (12, 13), (55, 16), (65, 16), (70, 17), (45, 8), (83, 6), (0, 10), (52, 7), (66, 8), (4, 11), (74, 13), (61, 10), (13, 16), (48, 13), (6, 4), (87, 8), (99, 8), (8, 8), (79, 8), (80, 6), (91, 10), (16, 10), (30, 15), (89, 11), (20, 12), (46, 13), (56, 7), (69, 7), (60, 7), (40, 14), (63, 12), (14, 10), (58, 10), (57, 13), (71, 7), (85, 7), (35, 6), (51, 12), (9, 9), (97, 7), (17, 13), (18, 13), (32, 8), (28, 15), (50, 8), (47, 9), (78, 11), (29, 5), (100, 9), (96, 8), (92, 13), (37, 9), (53, 11), (76, 13), (75, 10), (31, 14), (2, 16), (68, 14), (34, 7), (94, 10), (10, 8), (39, 10), (90, 9), (64, 7), (1, 9), (7, 10), (33, 15), (21, 5), (26, 6), (81, 8), (15, 7), (72, 13), (23, 15), (93, 5), (82, 13), (95, 10), (59, 9), (88, 8), (24, 11), (19, 13), (36, 6), (41, 8), (11, 8), (22, 6), (44, 10), (84, 3), (73, 9), (3, 7), (25, 9), (38, 9), (67, 7)]

Result: Implementing MapReduce program that processes a weather dataset is executed successfully.

EXP NO: 4	**Collect sensor data from any real time application and apply preprocessing techniques**
Date:	

Aim: The aim is to Collect sensor data from any real time application and apply preprocessing techniques.

Procedure:

Preprocessing sensor data is a crucial step in preparing it for further analysis or machine learning. Let's walk through the process using Python:

1. **Import Necessary Libraries**: First, import the required libraries such as Pandas, NumPy, and Scikit-Learn. These will help you manipulate and preprocess the data effectively

2. **Python** *import pandas as pd import numpy as np from sklearn.preprocessing import MinMaxScaler import seaborn as sns import matplotlib.pyplot as plt*

3. **Load the Dataset**: Load your sensor data into a Pandas DataFrame. For example, if you have a CSV file, you can read it like this: **Python**

   df = pd.read_csv('path/to/your/sensor_data.csv')
   print(df.head())

   This will display the first few rows of your dataset.

4. **Data Cleaning and Preprocessing**:
   - Handle missing values: Identify and handle any missing data (e.g., replace with mean, median, or drop rows/columns). ○ Remove irrelevant columns: Drop any columns that aren't useful for your analysis.
   - Convert data types: Ensure that data types are appropriate for each feature (e.g., numeric, categorical).

5. **Feature Scaling**: Normalize or standardize your features to bring them to a similar scale. For example, use Min-Max scaling:

6. **Exploratory Data Analysis (EDA)**: Visualize your data using libraries like Seaborn and Matplotlib. Explore relationships between features and identify outliers.

7. **Feature Engineering**: Create new features if needed. For instance, derive additional features from existing ones (e.g., ratios, averages).

8. **Handling Categorical Variables**: If your data contains categorical variables, encode them.

9. **Split Data into Training and Test Sets**: Divide your dataset into training and test subsets for model evaluation.

Code:

```
import random

# Function to generate a simple weather dataset def
generate_weather_data(num_records):
    weather_data = []     for _ in range(num_records):
temperature = random.randint(-20, 40) # Temperature in Celsius
humidity = random.randint(0, 100)      # Humidity in percentage
weather_data.append((temperature, humidity))     return
weather_data

# Function to apply preprocessing techniques def
preprocess(data):
    preprocessed_data = []     for
temperature, humidity in data:
        # Example preprocessing: Filtering out temperatures below 0
if temperature >= 0:
            # Example preprocessing: Normalizing humidity to range [0, 1]
humidity_normalized = humidity / 100.0
            preprocessed_data.append((temperature, humidity_normalized))
return preprocessed_data

if __name__ == '__main__':
    # Generate a simple weather dataset
weather_data = generate_weather_data(1000)

    # Apply preprocessing techniques
    preprocessed_data = preprocess(weather_data)

    # Print preprocessed data     print
("Preprocessed Weather Data:")     for
temperature, humidity in preprocessed_data:
        print (f"Temperature: {temperature}°C, Humidity: {humidity}")
```

OUTPUT:

Preprocessed Weather Data:
Temperature: 37°C, Humidity: 0.68

Temperature: 39°C, Humidity: 0.31
Temperature: 33°C, Humidity: 0.76
Temperature: 24°C, Humidity: 0.88
Temperature: 21°C, Humidity: 0.06
Temperature: 24°C, Humidity: 0.83
Temperature: 38°C, Humidity: 0.31
Temperature: 22°C, Humidity: 0.84
Temperature: 0°C, Humidity: 0.11
Temperature: 35°C, Humidity: 0.95
Temperature: 10°C, Humidity: 0.7
Temperature: 0°C, Humidity: 0.53
Temperature: 12°C, Humidity: 0.94
Temperature: 12°C, Humidity: 0.9
Temperature: 28°C, Humidity: 0.18
Temperature: 34°C, Humidity: 0.79
Temperature: 6°C, Humidity: 0.28
Temperature: 40°C, Humidity: 0.96
Temperature: 5°C, Humidity: 0.5
Temperature: 22°C, Humidity: 0.68
Temperature: 17°C, Humidity: 0.74
Temperature: 33°C, Humidity: 0.72
Temperature: 29°C, Humidity: 0.97
Temperature: 4°C, Humidity: 0.96
Temperature: 3°C, Humidity: 0.52
Temperature: 7°C, Humidity: 0.35
Temperature: 11°C, Humidity: 0.02
Temperature: 34°C, Humidity: 0.25
Temperature: 21°C, Humidity: 0.77
Temperature: 40°C, Humidity: 0.07
Temperature: 31°C, Humidity: 0.14
Temperature: 36°C, Humidity: 0.15
Temperature: 6°C, Humidity: 0.51
Temperature: 22°C, Humidity: 0.26
Temperature: 3°C, Humidity: 0.77

Result: Collecting sensor data from any real time application and apply preprocessing techniques is executed successfully.

EXP NO: 5	Collect sensor data and do Prediction using linear regression
Date:	

Aim: The aim is to Collect sensor data and do Prediction using linear regression.

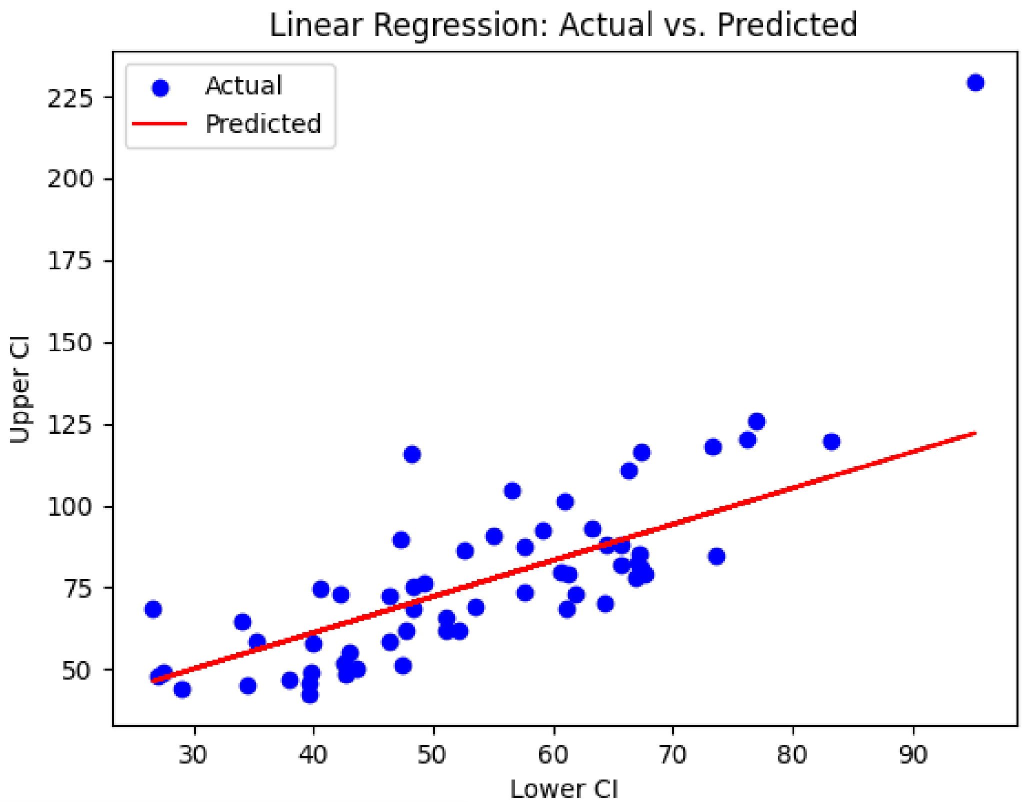
Procedure:

- We load the weather dataset using **pd.read_csv()** from **pandas**.
- We extract the humidity as the feature (**X**) and temperature as the target variable (**y**).
- We split the dataset into training and testing sets using **train_test_split** from **scikit-learn**.
- We produce relationship between one or more variables using Linear Regression.
- We train a model using a linear regression.
- We use the trained model to make predictions on the test data.
- Finally, we plot the actual vs. predicted values to visualize the performance of the Linear regression model.

Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
# Load weather dataset
weather_data = pd.read_csv('/content/cancer_updated.csv')
# Extract features (humidity) and target variable (temperature)
X = weather_data[['Lower CI']]
y = weather_data['Upper CI']
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
# Train linear regression model
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
# Make predictions
y_pred = lin_reg.predict(X_test)
# Plot the actual vs. predicted values
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.plot(X_test, y_pred, color='red', label='Predicted')
plt.xlabel('Lower CI')
plt.ylabel('Upper CI')
plt.title('Linear Regression: Actual vs. Predicted')
plt.legend()
plt.show()
```

OUTPUT:



Result: Collecting sensor data and predicting using linear regression is executed successfully.

EXP NO: 6	Collect sensor data and Implement Support Vector Machine
Date:	

Aim: The aim is to collect sensor data from the IoT devices and Implement SVM for classification or prediction.

Procedure:

- We load the weather dataset using **pd.read_csv()** from **pandas**.
- We extract the humidity as the feature (**X**) and temperature as the target variable (**y**).
- We split the dataset into training and testing sets using **train_test_split** from **scikit-learn**.
- We standardize the features using **StandardScaler** to ensure that each feature has a mean of 0 and a standard deviation of 1.
- We train a Support Vector Machine (SVM) model with a linear kernel (**kernel='linear'**).
- We use the trained model to make predictions on the test data.
- Finally, we plot the actual vs. predicted values to visualize the performance of the SVM model.

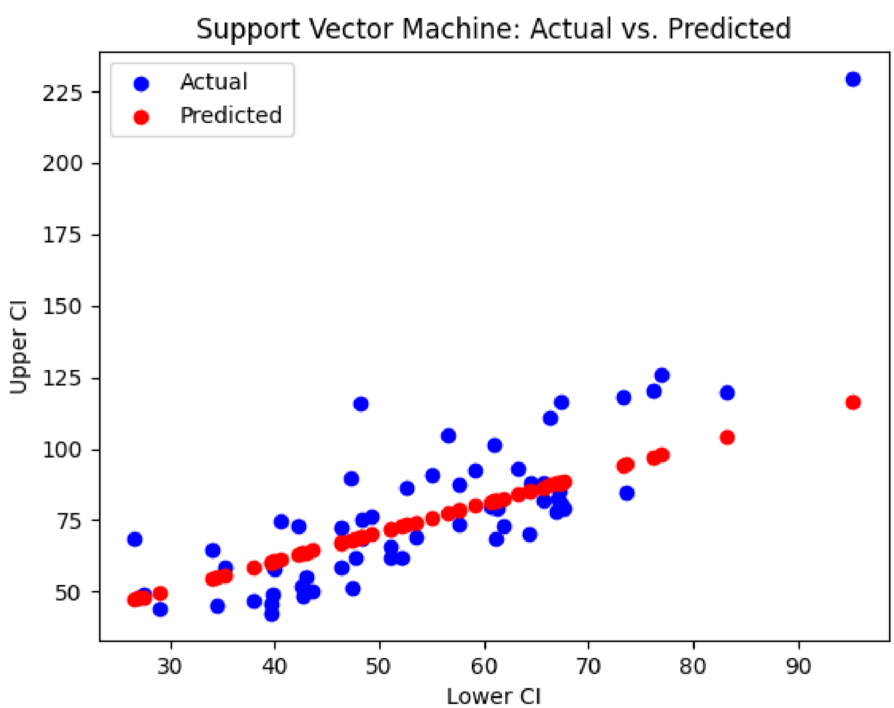
Note: Make sure to replace **'weather_data.csv'** with the path to your weather dataset CSV file.

Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

# Load weather dataset
weather_data = pd.read_csv('/content/cancer_updated.csv')
# Extract features (humidity) and target variable (temperature)
X = weather_data[['Lower CI']]
y = weather_data['Upper CI']

# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Standardize features
```

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train Support Vector Machine (SVM) model
svm_model = SVR (kernel='linear') # Linear kernel
svm_model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = svm_model.predict(X_test_scaled)
plt.scatter(X_test, y_test, color='blue', label='Actual')
plt.scatter(X_test, y_pred, color='red', label='Predicted')
plt.xlabel('Lower CI')
plt.ylabel('Upper CI')
plt.title('Support Vector Machine: Actual vs. Predicted')
plt.legend()
plt.show()
```

OUTPUT:



Result: Collecting sensor data and Implementing Support Vector Machine is executed successfully.

EXP NO: 7	Collect sensor data and Implement Decision tree classification technique
Date:	

AIM: The aim is to collect sensor data and Implement Decision tree Classification.

Procedure:

- We load the weather dataset using **pd.read_csv()** from **pandas**.
- We define the features (**X**) as 'Temperature' and 'Humidity', and the target variable (**y**) as 'Weather'.
- We split the dataset into training and testing sets using **train_test_split** from **scikit-learn**.
- We train a Decision Tree classifier using **DecisionTreeClassifier**.
- We make predictions on the test data using the trained model.
- We evaluate the model's performance using accuracy, classification report, and confusion matrix.

Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix
# Load weather dataset
weather_data = pd.read_csv('/content/cancer_updated.csv')
# Define features (X) and target variable (y)
X = weather_data[['Lower CI', 'Upper CI']]
y = weather_data['Recent Trend']
# Split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
# Train Decision Tree classifier
dt_classifier = DecisionTreeClassifier(random_state=42)
dt_classifier.fit(X_train, y_train)
# Make predictions
y_pred = dt_classifier.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
# Display classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))
# Display confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

OUTPUT:

```
Accuracy: 0.6833333333333333
Classification Report:
              precision    recall  f1-score   support

     falling       0.25      0.40      0.31         5
      rising       0.20      0.14      0.17         7
      stable       0.81      0.79      0.80        48

    accuracy                           0.68        60
   macro avg       0.42      0.44      0.42        60
weighted avg       0.69      0.68      0.69        60

Confusion Matrix:
[[ 2  0  3]
 [ 0  1  6]
 [ 6  4 38]]
```

Result: Collecting sensor data and Implementing Decision tree classification technique is executed successfully.

EXP NO: 8	Collect sensor data and Implement clustering algorithm
Date:	

AIM: The aim is to collect sensor data and Implement clustering algorithm.

Procedure:

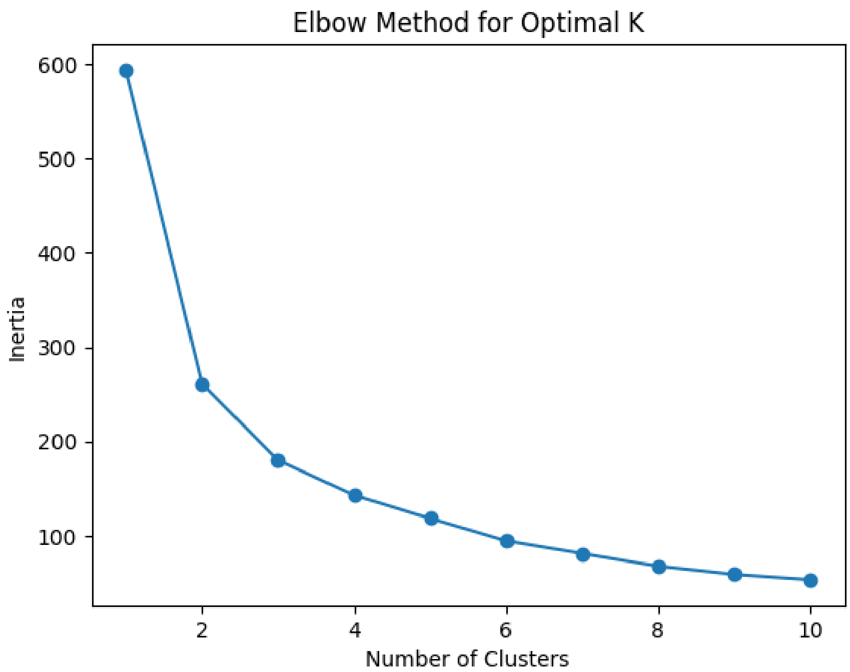
- We load the weather dataset using **pd.read_csv()**.
- We select features such as tempera humidity.
- We standardize the features using **StandardScaler** to ensure that each feature has a mean of 0 and a standard deviation of 1.
- We use the Elbow method to determine the optimal number of clusters.
- Based on the Elbow method, we choose the optimal number of clusters.
- We apply KMeans clustering with the chosen number of clusters.
- We add cluster labels to the dataset.
- Finally, we plot the clusters and centroids using matplotlib.

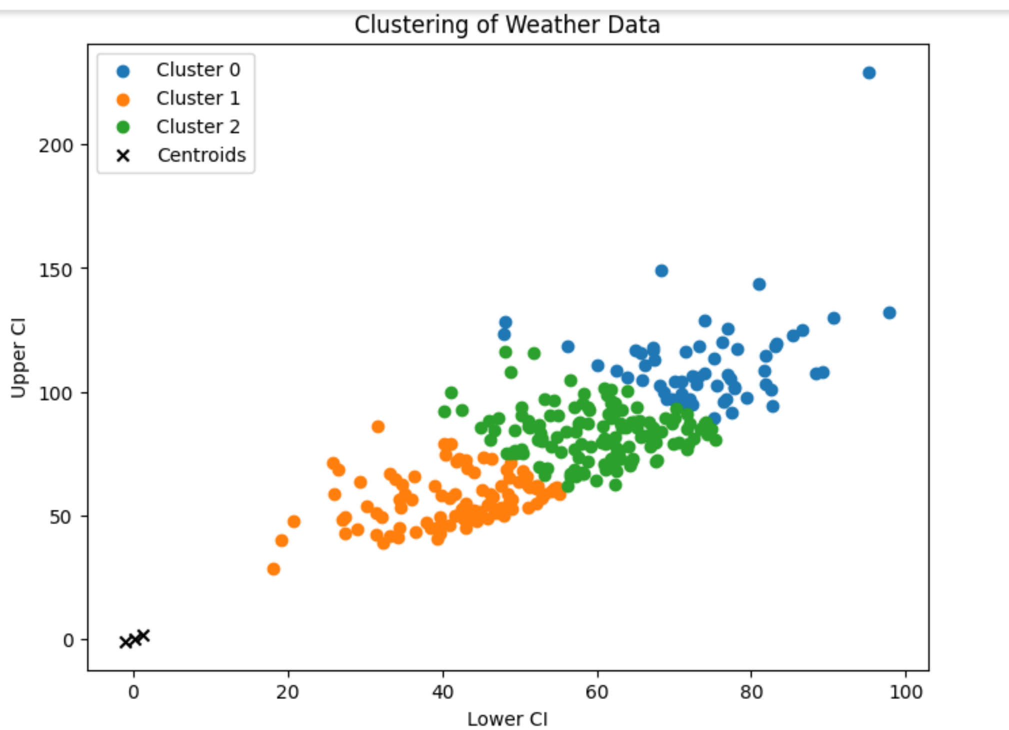
Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# Load weather dataset
weather_data = pd.read_csv('/content/cancer_updated.csv')
# Define features (X) and target variable (y)
X = weather_data[['Lower CI', 'Upper CI']]

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Determine the optimal number of clusters using the Elbow method
inertia = []
for n_clusters in range(1, 11):
    kmeans = KMeans(n_clusters=n_clusters, random_state=42)
    kmeans.fit(X_scaled)
    inertia.append(kmeans.inertia_)
```

```python
# Plot the Elbow method to determine the optimal number of clusters
plt.plot(range(1, 11), inertia, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal K')
plt.show()

# Based on the Elbow method, let's choose the optimal number of clusters
(e.g., 3 or 4)

# Apply KMeans clustering
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=42)
kmeans.fit(X_scaled)
labels = kmeans.labels_
centers = kmeans.cluster_centers_

# Add cluster labels to the dataset
weather_data['Cluster'] = labels

# Plot the clusters
plt.figure(figsize=(8, 6))
for cluster in range(n_clusters):
    cluster_data = weather_data[weather_data['Cluster'] == cluster]
    plt.scatter(cluster_data['Lower CI'], cluster_data['Upper CI'],
label=f'Cluster {cluster}')
plt.scatter(centers[:, 0], centers[:, 1], color='black', marker='x',
label='Centroids')
plt.xlabel('Lower CI')
plt.ylabel('Upper CI')
plt.title('Clustering of Weather Data')
plt.legend()
plt.show()
```

OUTPUT:





Result: Collecting sensor data and Implementing clustering algorithm is executed successfully.

EXP NO: 9	Visualize data using visualization techniques
Date:	

AIM: The aim is to visualize data using visualization techniques.

Procedure:

- We load the weather dataset using **pd.read_csv()** from **pandas**.
- We display the first few rows of th atistics of numerical variables using **head()** and **describe()** functions, respectively.
- We visualize the distribution of temperature and humidity using histograms.
- We create a scatter plot of temperature vs. humidity to explore their relationship.
- We plot box plots to visualize the distribution of temperature for different weather conditions.
- We use a pairplot to visualize pairwise relationships between different variables in the dataset.

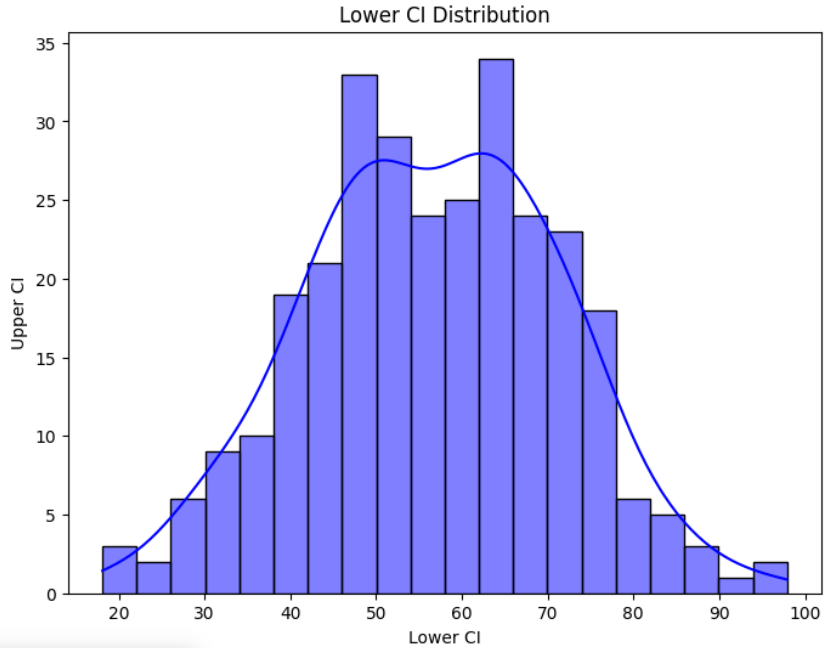
Code:

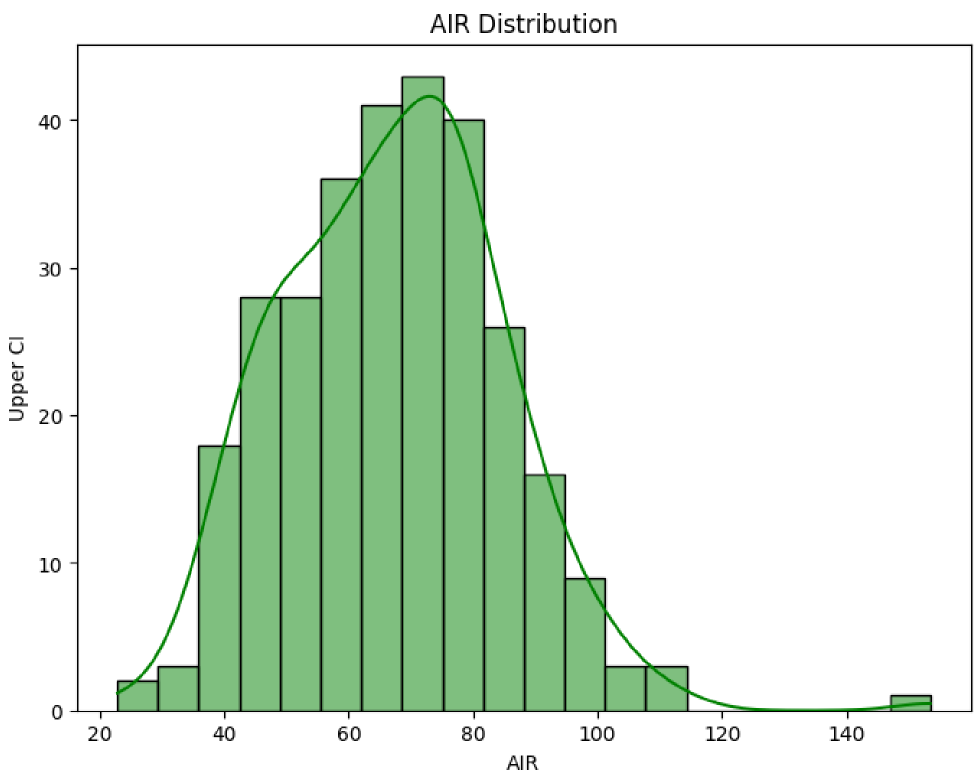
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Load weather dataset
weather_data = pd.read_csv('/content/cancer_updated.csv')

# Display the first few rows of the dataset
print("First few rows of the dataset:")
print(weather_data.head())

# Summary statistics of numerical variables
print("\nSummary statistics of numerical variables:")
print(weather_data.describe())

# Histogram of temperature distribution
plt.figure(figsize=(8, 6))
sns.histplot(weather_data['Lower CI'], bins=20, kde=True, color='blue')
plt.xlabel('Lower CI')
plt.ylabel('Upper CI')
plt.title('Lower CI Distribution')
plt.show()

# Histogram of humidity distribution
plt.figure(figsize=(8, 6))

sns.histplot(weather_data['AIR'], bins=20, kde=True, color='green')
```

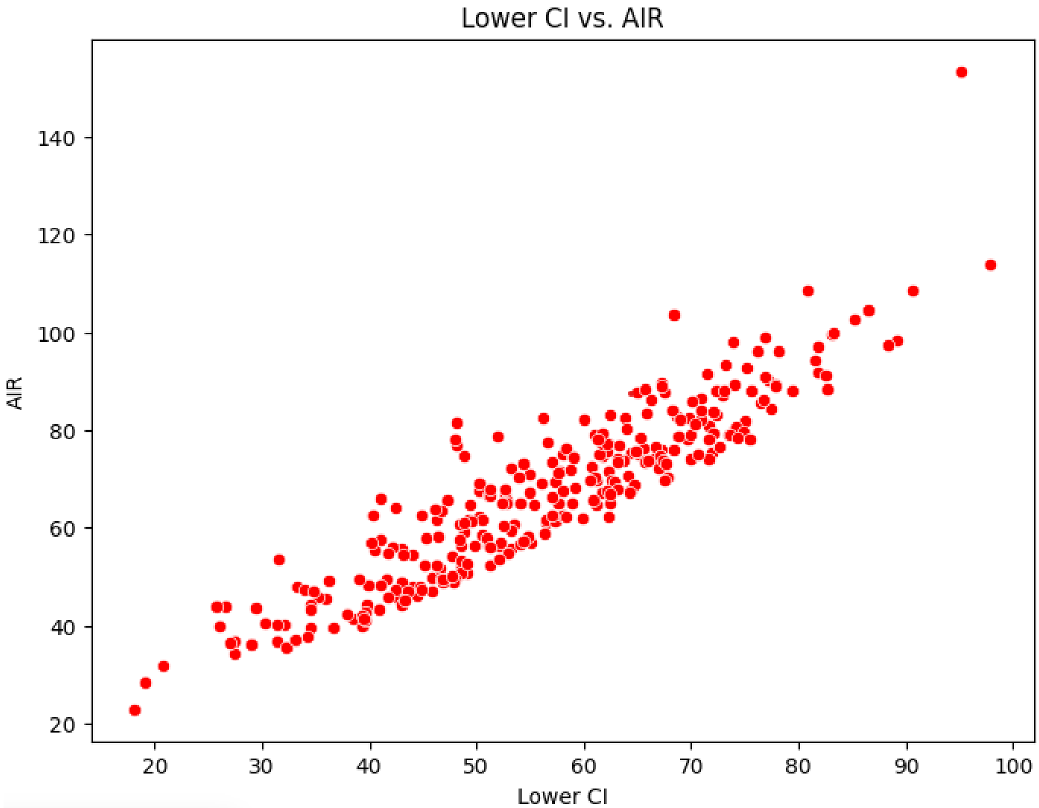
```python
plt.xlabel('AIR')
plt.ylabel('Upper CI')
plt.title('AIR Distribution')
plt.show()

# Scatter plot of temperature vs. humidity
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Lower CI', y='AIR', data=weather_data, color='red')
plt.xlabel('Lower CI')
plt.ylabel('AIR')
plt.title('Lower CI vs. AIR')
plt.show()
plt.figure(figsize=(10, 6))
sns.boxplot(x='Recent Trend', y='Lower CI', data=weather_data)
plt.xlabel('Recent Trend Condition')
plt.ylabel('Lower CI')
plt.title('Lower CI by Recent Trend Condition')
plt.show()
sns.pairplot(weather_data, diag_kind='kde')
plt.suptitle('Pairwise Relationships')
plt.show()
```

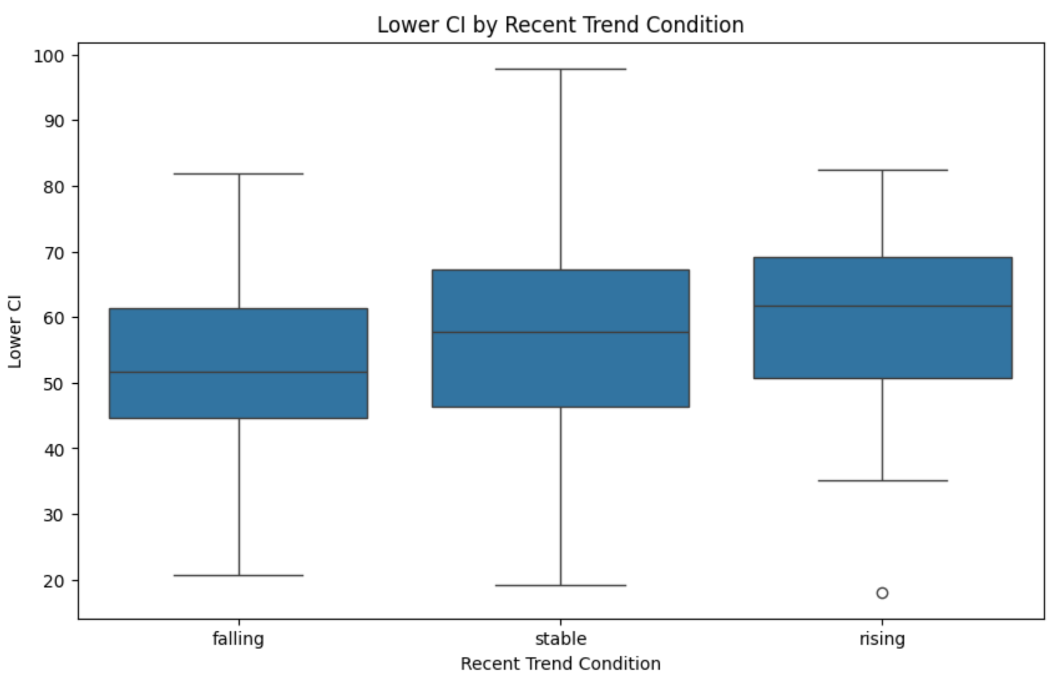
OUTPUT:

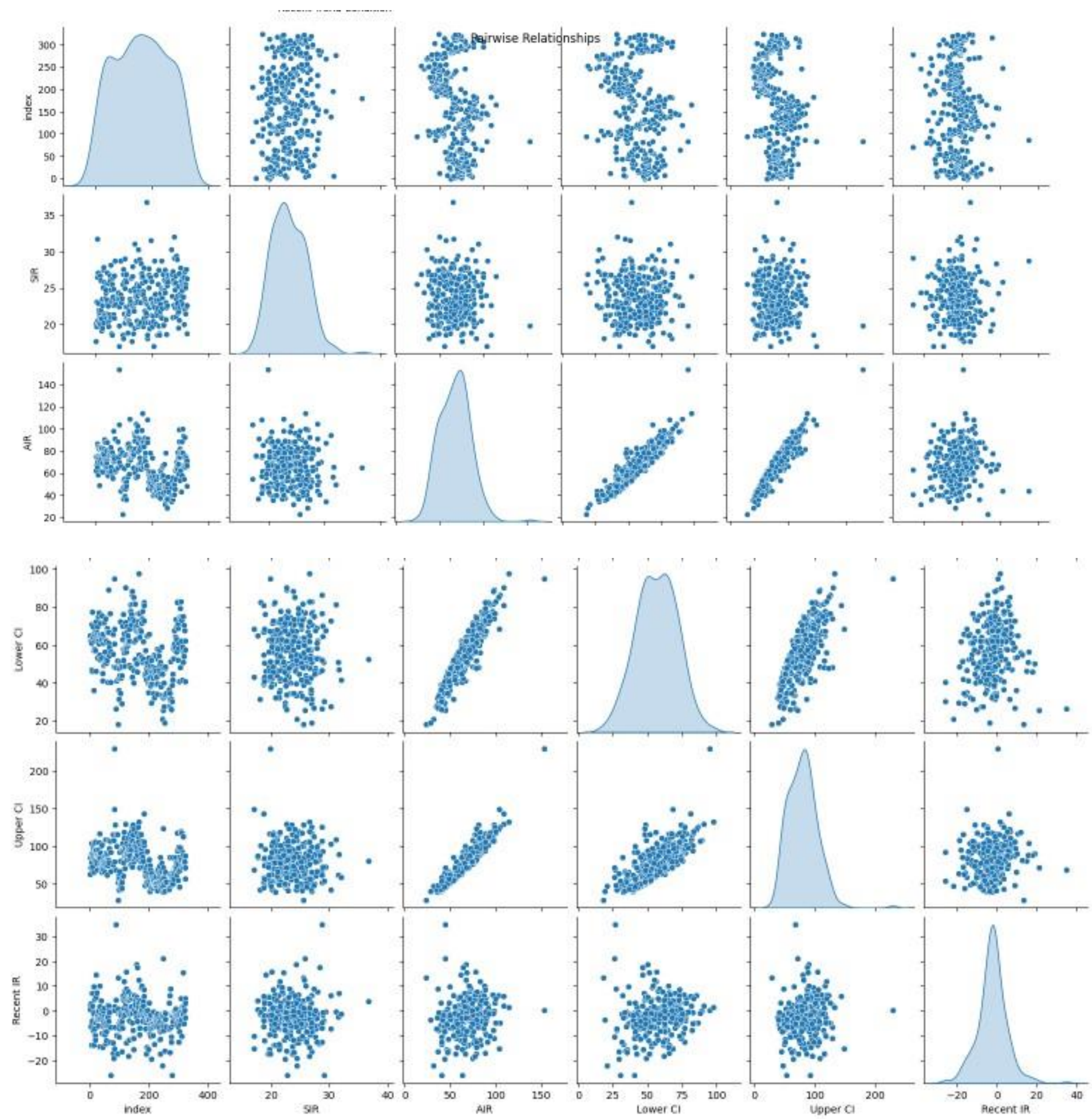
```
First few rows of the dataset:
   index                          County   SIR   AIR  Lower CI  Upper CI  \
0      0            US (SEER+NPCR)(1,10)  20.1  62.4      62.3      62.6
1      1  Autauga County, Alabama(6,10)  17.7  74.9      65.1      85.7
2      2  Baldwin County, Alabama(6,10)  19.7  66.9      62.4      71.7
3      3  Barbour County, Alabama(6,10)  23.1  74.6      61.8      89.4
4      4     Bibb County, Alabama(6,10)  26.5  86.4      71.0     104.2

  Recent Trend  Recent IR        Date
0      falling        2.5  01-01-2013
1       stable        0.5  02-01-2013
2       stable        3.0  03-01-2013
3       stable       -6.4  04-01-2013
4       stable       -4.5  05-01-2013

Summary statistics of numerical variables:
            index         SIR         AIR    Lower CI    Upper CI   Recent IR
count  297.000000  297.000000  297.000000  297.000000  297.000000  297.000000
mean   161.646465   23.585017   67.169024   56.587879   79.905051   -2.450168
std     94.505253    3.080901   17.617418   14.731830   23.971454    7.361400
min      0.000000   17.000000   22.900000   18.100000   28.500000  -26.100000
25%     83.000000   21.200000   54.400000   46.600000   61.800000   -6.100000
50%    162.000000   23.400000   67.500000   57.100000   79.500000   -2.300000
75%    239.000000   25.800000   78.400000   67.200000   94.300000    1.100000
max    324.000000   36.800000  153.400000   97.900000  229.400000   34.900000
```


Lower CI Distribution
Upper CI
Lower CI
0
5
10
15
20
25
30
35
20
30
40
50
60
70
80
90
100


AIR Distribution
Upper CI
AIR
0
10
20
30
40
20
40
60
80
100
120
140


Lower CI vs. AIR
AIR
140
120
100
80
60
40
20
20
30
40
50
60
70
80
90
100
Lower CI


Lower CI by Recent Trend Condition
Lower CI
100
90
80
70
60
50
40
30
20
falling
stable
rising
Recent Trend Condition



Result: Visualizing data using visualization techniques is executed successfully.

EXP NO: 10	Model Time series data
Date:	

AIM: The aim is to analyze the Time series data by using ARIMA Model.

Procedure:

Modeling time series data involves analyzing and forecasting data points based on their temporal order. One popular method for time series forecasting is using Autoregressive Integrated Moving Average (ARIMA) models.

- We load the time series data from a CSV file using **pd.read_csv()** from **pandas**.
- We convert the 'Date' column to datetime format and set it as the index of the DataFrame.
- We plot the time series data to visualize its pattern and trends.
- We plot autocorrelation and partial autocorrelation plots to determine the appropriate parameters for the ARIMA model.
- We fit an ARIMA model to the time series data using the specified order **(p, d, q)**.
- We print the summary of the ARIMA model to examine its coefficients and statistical information.
- We plot the residuals of the model to check for any patterns or trends.
- We forecast future values using the trained ARIMA model and plot the original data along with the forecasted values.

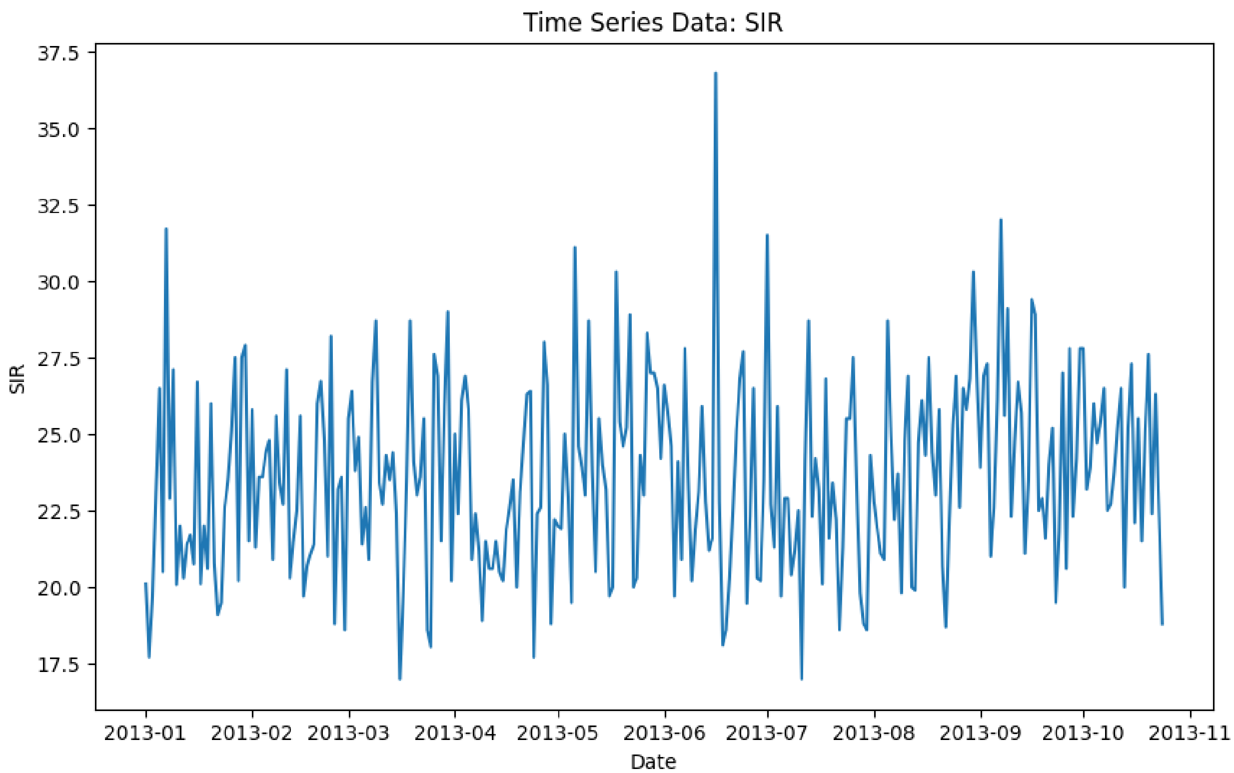
Code:

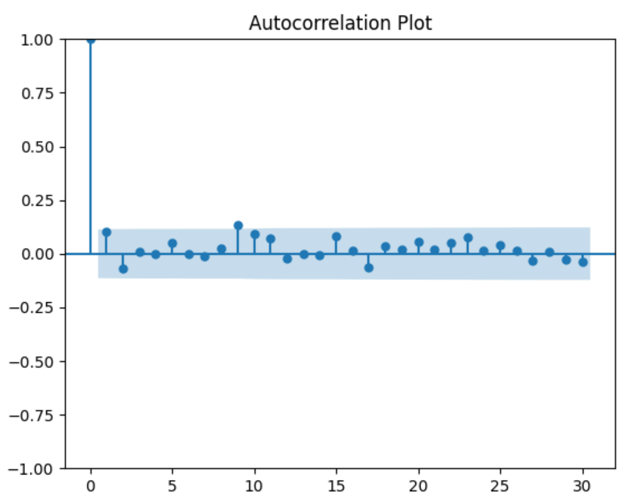
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

# Load time series data
data = pd.read_csv('/content/cancer_updated.csv')

# Convert the 'Date' column to datetime format and set it as the index
data['Date'] = pd.to_datetime(data['Date'], format='%d-%m-%Y')

# Drop rows with missing dates
data.dropna(subset=['Date'], inplace=True)

# Set the index to the 'Date' column
data.set_index('Date', inplace=True)
```

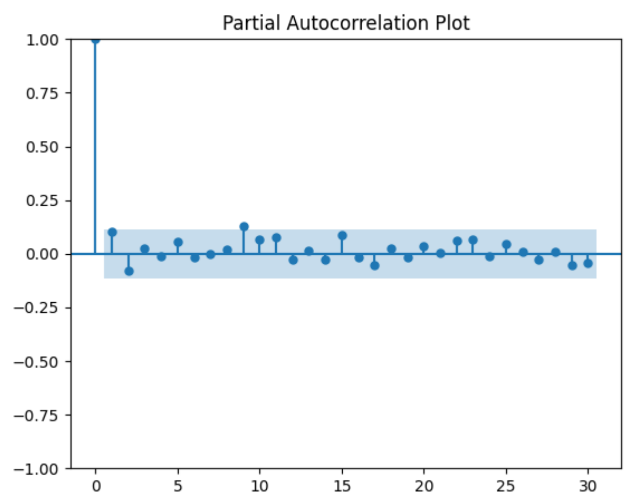
```
# Select only the first 400 columns for analysis
data_selected = data.iloc[:, :400]

# Plot original 'SIR' time series data against selected dates
plt.figure(figsize=(10, 6))
plt.plot(data_selected.index, data_selected['SIR']) # Plotting 'SIR' against
selected dates
plt.title('Time Series Data: SIR')
plt.xlabel('Date')
plt.ylabel('SIR')
plt.show()

# Plot autocorrelation and partial autocorrelation plots for 'SIR' column
plt.figure(figsize=(14, 5))
plt.subplot(1, 2, 1)
plot_acf(data_selected['SIR'], lags=30, ax=plt.gca())
plt.title('Autocorrelation Plot')
plt.subplot(1, 2, 2)
plot_pacf(data_selected['SIR'], lags=30, ax=plt.gca())
plt.title('Partial Autocorrelation Plot')
plt.show()

# Fit ARIMA model
order = (2, 1, 1) # (p, d, q)
model = ARIMA(data_selected['SIR'], order=order)
result = model.fit()
print(result.summary())

# Plot model residuals
plt.figure(figsize=(10, 6))
plt.plot(result.resid)
plt.title('Model Residuals')
plt.xlabel('Date')
plt.ylabel('Residuals')
plt.show()

# Forecast future values
forecast_steps = 12 # Number of steps to forecast
forecast = result.forecast(steps=forecast_steps)

plt.figure(figsize=(10, 6))
plt.plot(data_selected.index, data_selected['SIR'], label='Original Data')
plt.plot(pd.date_range(start=data_selected.index[-1],
periods=forecast_steps+1, freq='M')[1:], forecast, label='Forecasted
Values', linestyle='--')
plt.title('Original Data vs Forecasted Values')
plt.xlabel('Date')
```

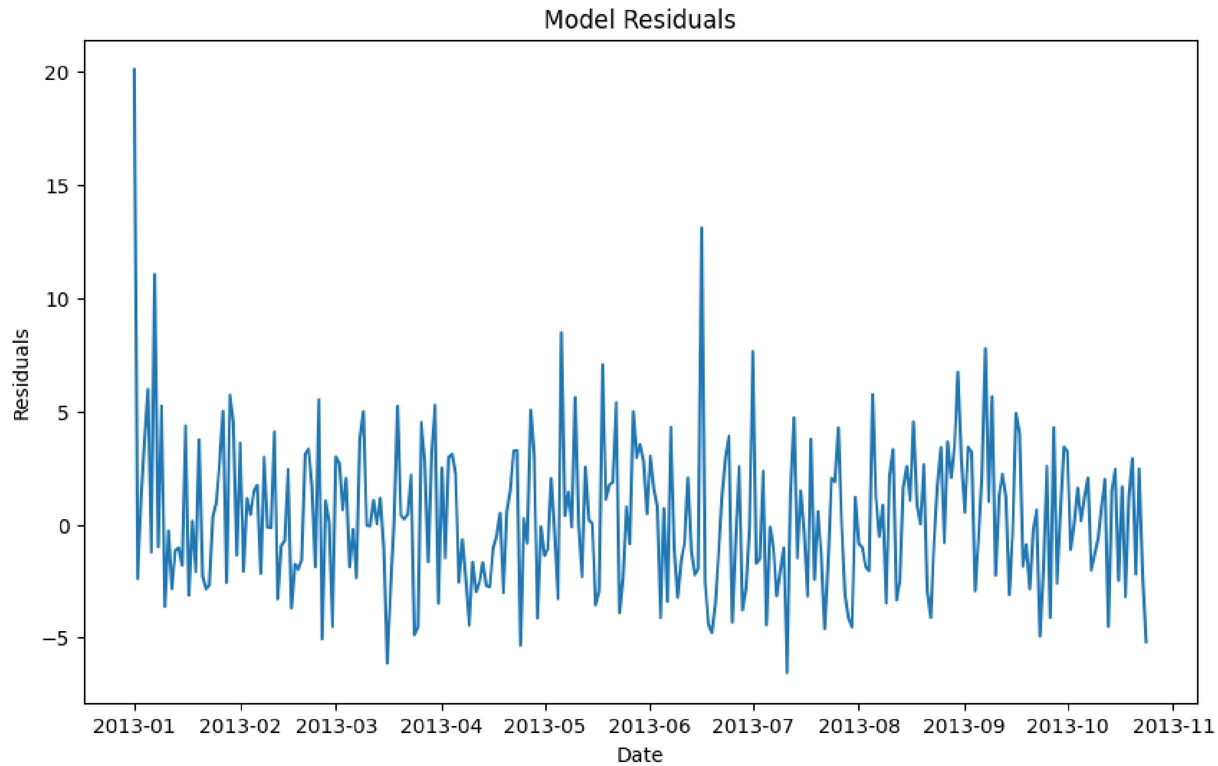
```
plt.ylabel('SIR')
plt.legend()
plt.show()
```

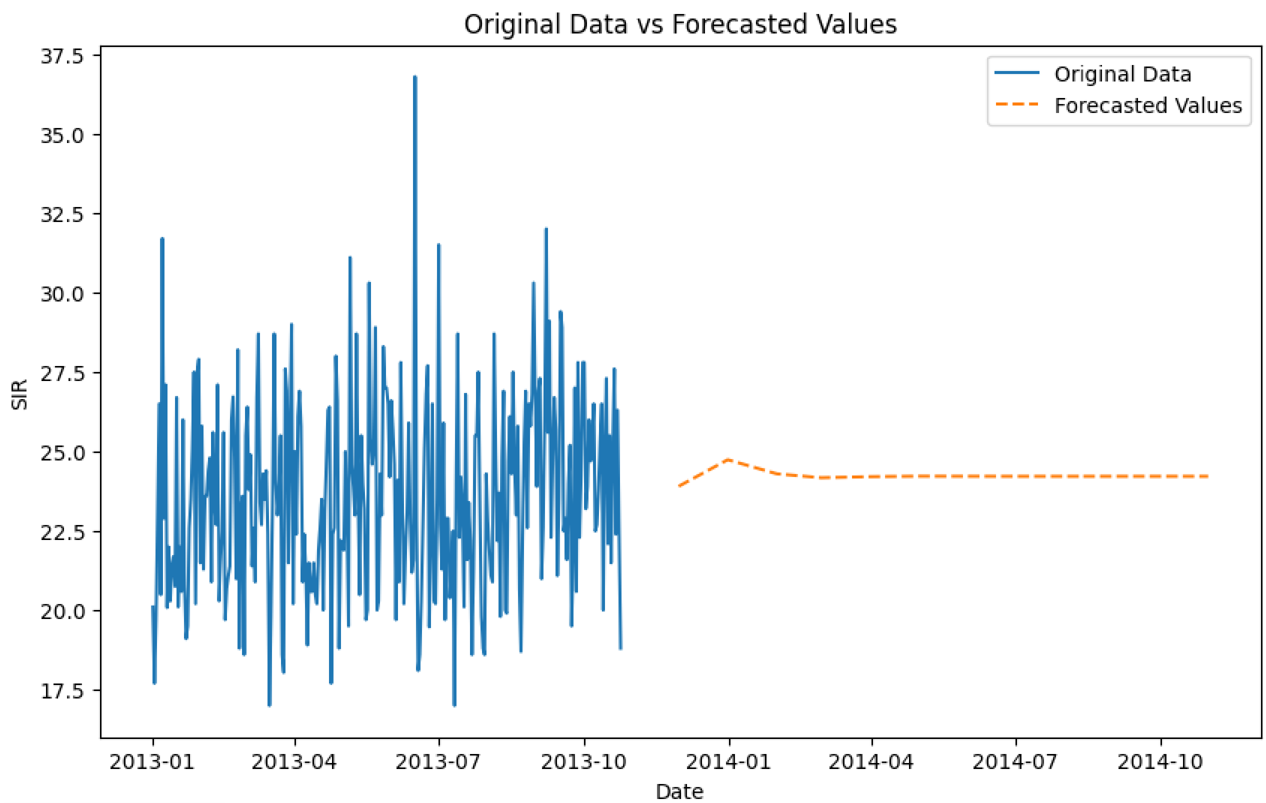
OUTPUT:











Result: Modeling time series data involves analyzing and forecasting data points based on their temporal order is executed successfully.

EXP NO: 11	Implement an application that stores big data in HBase/ MongoDB/ Pig
Date:	

Aim: Aim to implement an application that stores big data in Hbase/ MongoDB/ Pig.

Procedure:

1. **Installation**:

   - First, ensure you have access to a MongoDB database. You can download a free MongoDB database from here or use a MongoDB cloud service like MongoDB Atlas.
   - Next, install the **PyMongo** driver using pip. If you haven't already, open your command line and run the following command:

   - python -m pip install pymongo

2. **Test PyMongo**:

   - To verify that the installation was successful, create a Python file (let's call it demo_mongodb_test.py) with the following content:

   Python

```
# demo_mongodb_test.py import
pymongo
# Test if pymongo is installed
print("PyMongo is installed and ready to be used.")
```

   - Execute the above code. If no errors occur, you're all set to use PyMongo!

3. **Basic CRUD Operations**:

   - With PyMongo, you can perform the following operations:

1. **Create**: Insert data into MongoDB.
2. **Read**: Retrieve data from MongoDB.
3. **Update**: Modify existing data.
4. **Delete**: Remove data from MongoDB.

Example Usage:

Here's a simple example of inserting data into a MongoDB collection:

```
import pymongo # Connect to MongoDB client

=pymongo.MongoClient("mongodb://localhost:27017/") db =

client["mydatabase"] collection = db["mycollection"]


# Insert a document data =

{"name": "John", "age": 30}

collection.insert_one(data)
```

OUTPUT:

Successful Insertion: ObjectId('63e8d287f49e8a0f228b4567')

Data inserted successfully.

Result: Implementing an application that stores big data in Hbase/ MongoDB/ Pig

is executed successfully.

EXP NO: 12	Implement an application for predicting air pollution level using gas sensors.
Date:	

Aim: The aim is to Implement an application for predicting air pollution level using gas sensors.

Procedure:

Step 1: Prepare Your Environment

First, ensure you have the necessary libraries installed. If not, install them using pip:

pip install numpy pandas scikit-learn matplotlib

Step 2: Sample Dataset

Imagine we have a CSV file named **air_quality.csv** with sensor readings for CO, NO2, and O3, alongside the target variable PM2.5 (particulate matter size 2.5 which is a common measure for air pollution levels).

CO,NO2,O3,PM2.5
0.4,0.02,0.03,12
0.25,0.01,0.02,9
0.5,0.03,0.04,15
...

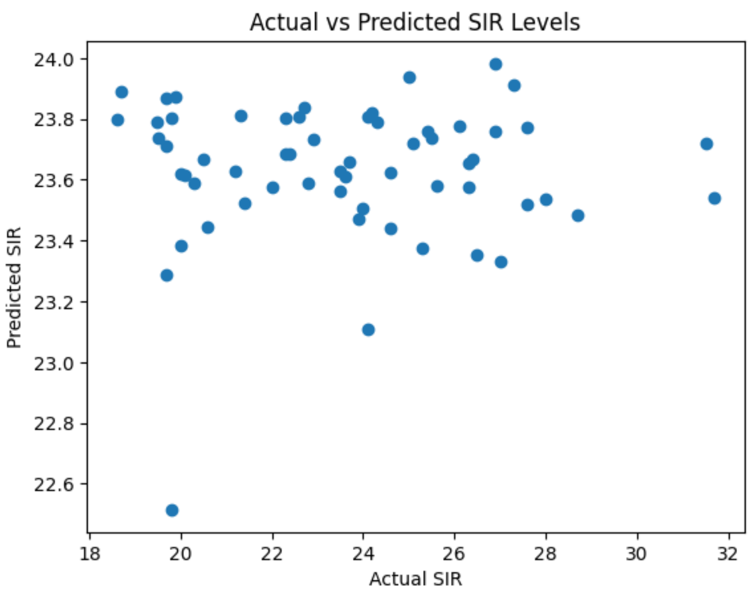
Python Code:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import numpy as np
import matplotlib.pyplot as plt

# Load the dataset
df = pd.read_csv('/content/cancer_updated.csv')

# Select features and target
X = df[['AIR', 'Lower CI', 'Upper CI']]  # Features: Sensor readings
y = df['SIR']  # Target: PM2.5 levels

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Initialize and train the linear regression model

model = LinearRegression()
model.fit(X_train, y_train)
```

```
# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")

# Plotting actual vs. predicted values
plt.scatter(y_test, y_pred)
plt.xlabel("Actual SIR")
plt.ylabel("Predicted SIR")
plt.title("Actual vs Predicted SIR Levels")
plt.show()
```

OUTPUT:

```
Mean Squared Error: 9.633964847297674
Root Mean Squared Error: 3.1038628911886033
```



Result: Implementing an application for predicting air pollution level using gas sensors is executed successfully.